SKIN LESION DELINEATION: CHALLENGES AND METHODS

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A. Purpose and Motivation

Accurate skin lesion segmentation is a critical factor in computer-aided skin cancer detection systems. Different approaches have been applied on skin lesion boundary detection in the past years. However, it is hard to tell the performance of every method and hence is difficult to make a wise choice in computer-aided diagnosis.

In this study, we study and evaluate several state-of-the-art algorithms based on two evaluators F_{RC} and Hoummoude Distance.

B. Segmentation Methods

The segmentation method to do the comparison are categorized into supervised which involves initialization and unsupervised which finds skin lesion boundaries automatically.

• Unsupervised

K-Means

E-step :it labels pixel based on proximity to the cluster center

M-step :it re-computes the centers for each class with the same label

EM

E-step :it computes an expectation value of the complete data

M-step :it computes to estimate parameters by maximizing the log likelihood of the complete data

Graph Cut[3]

- Each image pixel is viewed as a vertex of a graph
- The similarity between two pixels is viewed as the weight of the edge of these two vertices
- Segmentation is achieved by cutting edges in the graph to form a good set of connect Components.

• Supervised

Active Contour(Chan-Vese)[1]

•Basic idea of active contour models or snakes is to evolve a curve, subject to constraints from a given image, in order to detect objects

Etotal=Einternal + Eexternal +Econstraint

•The energy terms should be defined cleverly in a way such that the final position of the contour will have minimum energy (minimization problem)

Random walk[2]

- random walk is an concept in stochastic process

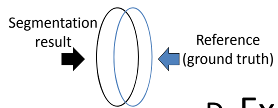
•After a random walk one could quickly determine the probability that each unlabeled pixel will reach to one of the pre-labeled pixels

C. Evaluation

Two methods are applied to evaluate segmentation results for accuracy. One is Hammoude metric (H) [4] which is based on a pixel by pixel comparison of the pixels enclosed by two boundaries and the other is , an evaluation criterion [5] which takes into account both the global intra-region homogeneity and the global inter-region disparity

•Hammoude Distance

$$dHam = \frac{\#(X \cup Y) - \#(X \cap Y)}{\#(X \cup Y)}$$



•RC Metric

$$D_{intra}(I) = \frac{1}{m}\sum m \frac{r_i}{NT} D_{intra}(R_i)$$

$$F(D_{intra}(I), D_{inter}(I)) = \left(\frac{D_{intra}(I) - D_{inter}(I)}{2}\right)$$

$$D(R_i, R_j) = \frac{|E[R_i] - E[R_j]|}{NG}$$

D. Experimental Setup

•Preprocessing

- Gaussian low pass filter to reduce noise
- A morphological filter using a disk as structuring element to remove dark skin hair

•Morphological closing is applied on segmented mask images to get smoother boundaries

•Skin lesion images are resized to one fourth to get faster computation

•Initialization

- For the active contour based method, the initialization of the contour of a skin lesion with a rectangular region or initial polygon is required
- For random walk, seeds should be selected beforehand. In this comparison study, two seeds for each region (lesion and background) are selected

E. Results

Active Contour, Expectation Maximization, K-Means, Graph cut and Random Walk based methods are applied on 6 lesion images with 10 repetitions. The averaged results for each of the six methods are given in figure 1.

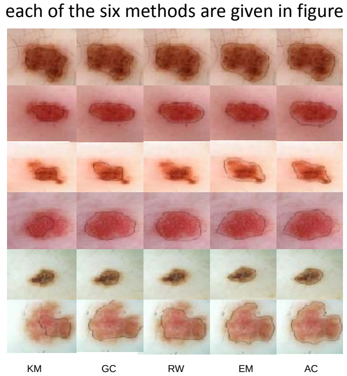


Fig.1. Examples of segmentation results.

Methods	H Mean Var	RC Mean Var	Time (s)
AC	**0.155 0.004**	**4.102 0.283**	16.659
RW	0.481 0.085	5.617 1.452	0.371
EM	0.240 0.017	4.162 0.339	2.703
GC	0.296 0.013	4.872 0.764	**0.202**
KM	0.582 0.010	5.829 0.506	1.688

Table 1. Evaluation using Hammoude distance and RC metric. The unsupervised methods are in the shaded rows

F. Conclusion

Active contour and EM perform better than graph cut, k-means and random walk based on six test images in terms of segmentation accuracy. Among these three methods, EM is more efficient, taking only 1.6883 seconds compared with AC (15.0347 s) and LS (52.3183 s). Although K-means is time efficient, the segmentation output is less acceptable.

G. Future Work

The blurry boundary is the problem to solve for better segmentation accuracy. In order to address the problem of fuzzy edge, we come up with an idea to learn the perception of human beings based on active contour models.

•Learning-based Model

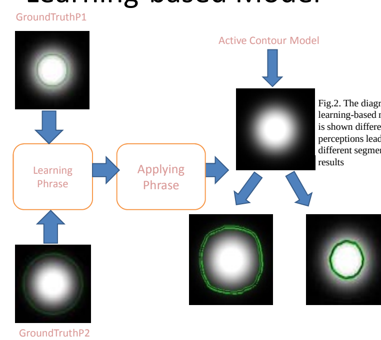


Fig.2. The diagram for the learning-based model. As it is shown different perceptions lead to different segmentation results

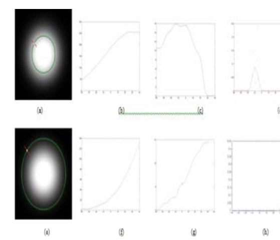


Fig.3. Process of the knowledge learning phrase. Column 1 shows two different human perceptions respectively with one set of pixels points in red on the normal direction of a point circled out in white on the boundary. Column 2 shows the intensity profile from each set of pixel points for the two different perceptions. Column 3 presents the first derivative of the intensity profile shown in column 2. Column 4 shows us the final learned curve (bias distribution) for the two different-perceptions ground truth.

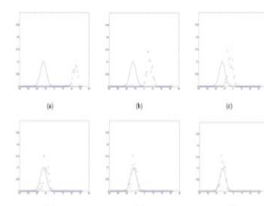


Fig.4 The process of the bias distribution of current evolving curve getting closer to the learned curve after different number of iterations. (a) shows the two distributions at the very beginning; (b) after 200 iterations; (c) after 400 iteration; (d) after 600 iterations; (e) after 800 iterations. (f) after 1000 iterations.

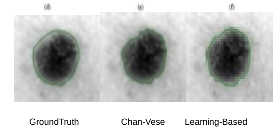


Fig.5. The segmentation results on the left shows the learning-based model is better than traditional Chan-Vese Model taking the ground truth as reference.

Reference

[1]T. F.Chan, and L. A. Vese, Active Contour without Edges. IEEE Trans. on Image Processing, v10, n2, pp266-276, FEB 2001
[2]L. Grady, Random Walks for Image Segmentation. IEEE Trans. on Pattern Analysis and Machine Intelligence, v28, n11, pp1768-1783, NOV.2006
[3]T. Cour, Florence Benezit, Jianbo Shi. Spectral Segmentation with Multiscale Graph Decomposition. IEEE International Conference on Computer Vision and Pattern Recognition, v2, pp.1124-1131, 2005
[4]Chalana and Y. Kim, A methodology for evaluation of boundary detection algorithms on medical images. IEEE Transactions on Medical Imaging, v16, n5, pp. 642-652, 1997
[5]H. Zhang, J. E.Fritts, S. A.Goldman, Image segmentation evaluation: A survey of unsupervised methods. Computer Vision and Image Understanding , v110, pp. 260-280, 2008